DECISION SUPPORT SYSTEM FOR MEDICAL THERAPY PLANNING

RELATED APPLICATION

[0001] The present patent document claims the benefit of the filing date under 35 U.S.C. § 119(e) of Provisional U.S. Patent Application Ser. Nos. 62/677,716, filed May 30, 2018, 62/745,712, filed Oct. 15, 2018, which are hereby incorporated by reference.

BACKGROUND

[0002] The present embodiments relate to decision support for therapy. One typical example is the application in radiotherapy. Radiotherapy is a useful and cost-effective treatment strategy for many types of cancer. Although radiotherapy is an effective cancer treatment, a large portion of patients subsequently experience radio-resistance and recurrence of their cancers. Doctors seek to select treatments based on specific characteristics of the patient and their disease to avoid treatment resistance and recurrence.

[0003] Predictors of radiation response are largely limited to clinical and histopathologic parameters. Molecular characterization using genomic and proteomic technologies is limited due to spatial and temporal heterogeneity of tumors. The tumors usually require biopsies and invasive surgeries to extract and analyze small portions of tumor tissue, which does not allow for a complete characterization of the tumor. Medical imaging can provide a more comprehensive view of the entire tumor in an ongoing basis to monitor the development and progression of the tumor or its response to therapy. Imaging is noninvasive and is already often repeated during treatment in routine practice.

[0004] Predictive information personalized to a patient may be extracted from medical imaging. One example is the treatment selection for non-small cell lung cancer (NSCLC). Stereotactic body radiation therapy (SBRT) is the standard of care for medically inoperable patients with early-stage NSCLC. However, different patterns of failure (local recurrence or distant recurrence) can be observed after SBRT. Moreover, when patients undergo repeat SBRT or salvage therapy, the outcomes are significantly worse. Standard approaches for radiotherapy that demonstrate efficacy for a population may not achieve optimal results for individual patients. An unmet clinical need is to predict as early as possible the potential outcome. For instance, if the patients are divided into two groups of responders and non-responders based on some prognostic or predictive biomarker, a series of strategies could be followed to further change the response pattern. The treatment parameters or treatment sequence and modality may be changed in the treatment strategy for patients in the non-responder group.

[0005] In clinical practice, tumor response to therapy is only measured using one- or two-dimensional descriptors of tumor size (RECIST and WHO, respectively). Although the tumor size measured in follow-up scans can indicate response to therapy, it often does not provide enough predictive information to the outcome of therapy.

[0006] In radiomics, digital medical images are converted to high dimensional data for improved decision support. The hypothesis is that biomedical images contain information that reflects underlying pathophysiology and that these relationships can be revealed via quantitative image analyses. The practice of radiomics typically involves extraction and qualification of descriptive features from the volume and application of a model to predict outcome from the descriptive image features. In classical radiomic analysis, the image features that can describe various tumor physical and geometrical characteristics are pre-defined and can be computed using different mathematical formulas (handcrafted features). These features usually quantify characteristics about tumor intensity, shape, texture, and wavelet transformation focusing on the frequency domain. The radiomics analysis may fail to maximize the information obtained where a very large number of features are usually extracted from images which contain lots of redundant or irrelevant information. Handcrafted radiomic features are in pre-defined groups so it is likely that some predictive information is not fully captured by the pre-defined features.

SUMMARY

[0007] Systems, methods, and instructions on computer readable media are provided for decision support in a medical therapy. Machine learning provides a machine-learned generator for generating a prediction of outcome for therapy personalized to a patient. Deep learning may result in features more predictive of outcome than handcrafted features. More comprehensive learning may be provided by using multi-task learning where one of the tasks (e.g., segmentation, non-image data, and/or feature extraction) is unsupervised and/or draws on a greater number of training samples than available for outcome prediction alone.

[0008] In a first aspect, a method is provided for decision support in a medical therapy system. The support is in the form of outcome prediction personalized to a patient. A medical scan of a patient is acquired. A prediction of outcome from therapy for the patient is generated by a machine-learned multi-task generator having been trained based with both image feature error and outcome error. An image of the outcome (e.g., a therapy failure risk score) is displayed for decision support.

[0009] The medical scan may be of any modality, such as scanning the patient with a computed tomography scanner. The scan may have any spatial extent in the patient, such as acquiring voxel data representing a three-dimensional distribution of locations in a volume of the patient. The outcome is generated based on input of the voxel data for a segmented or other three-dimensional region of the volume.

[0010] Various embodiments are provided for generating the outcome. The machine-learned multi-task generator may be a convolutional neural network; may have been trained with deep learning to create features compared to handcrafted radiomics features for the image feature error; may have been trained with a greater number of training data samples for the image feature error than for the outcome error; and may have been trained with a weighted combination of the image feature error and outcome error as a loss function. The outcome error may be a cross-entropy loss or partial likelihood loss function, and the image feature error may be a mean square loss function.

[0011] The outcome may be a likelihood of therapy failure or tumor recurrence. The outcome may be an estimated time to reoccurrence or death.

[0012] In one embodiment, the machine-learned multi-task generator is used to identify one or more outlier samples in training data. The machine-learned multi-task generator